Air Pollution and the Labor Market: Evidence from Wildfire Smoke[*]

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Abstract

We estimate labor market responses to transient air pollution events using a novel linkage of satellite images of wildfire smoke plumes to pollution monitor data and labor market outcomes in the United States. Smoke exposure reduces earnings in both the year of exposure and the following year, lowers labor force participation, and increases Social Security payments. With an average of 17.7 days of annual smoke exposure per person, earnings losses sum to 1.26 percent of annual labor income. We estimate that the welfare cost of these lost earnings exceeds the mortality cost of wildfire smoke.

JEL Classification: I10, J21, Q51, Q52, Q53, Q54
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Pollution imposes large costs on human well-being. Air pollution exposure increases infant and elderly mortality (Chay and Greenstone, 2003; Jayachandran, 2009; Deryugina et al., 2019) and reduces long-run health and future income among those exposed in utero and infancy (Sanders, 2012; Chen et al., 2013; Isen, Rossin-Slater and Walker, 2017). While infant and elderly health impacts are thought to constitute the vast majority of the welfare costs of poor air quality (U.S. Environmental Protection Agency, 2011; OECD, 2016), air pollution also negatively affects adult labor supply and productivity (Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015). It remains largely unknown, however, whether labor market effects constitute an important share of the overall costs of air pollution. Quantifying these effects matters greatly for understanding how pollution affects human welfare and for designing efficient pollution-abatement policies.

This paper examines the importance of air pollution in the determination of U.S. labor income. A key challenge for measuring the causal effect of air pollution on countrywide labor market outcomes is finding geographically widespread fluctuations in pollution that are not themselves driven by economic factors, such as regulations, that directly impact economic activity. To sidestep the joint determination of air quality and economic activity, our analysis leverages nationwide variation in U.S. air quality induced by wildfire smoke. Wildfires account for about 20 percent of the fine particulate matter emitted in the United States (U.S. Environmental Protection Agency, 2014). Wind can transport wildfire smoke for thousands of miles, generating plausibly exogenous air pollution events that are geographically dispersed and widespread (Langmann et al., 2009).

Our analysis relies on a novel linkage of high-resolution satellite remote sensing data on wildfire smoke plumes in the United States with ground pollution monitors and annual labor market data over the period 2006–2015.[1] We exploit year-over-year variation in wildfire smoke exposure in a given region to estimate the medium- to long-run impacts of air pollution events on labor market outcomes. We then benchmark the welfare cost of lost earnings due to wildfire smoke by comparing them to mortality effects estimated using the same research design, similar to how Deschênes, Greenstone and Shapiro (2017) gauge the cost of defensive investments.

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[1]We use wildfire smoke exposure data developed by Miller, Molitor and Zou (2017) and adapt it to fit the unit of analysis for the labor market data.

Several features of wildfire smoke combine to create a useful natural experiment for studying the effects of air quality on labor market outcomes. Wildfire-related smoke events occur frequently throughout the United States: from 2006–2015, nearly every U.S. county was exposed to wildfire smoke, with a population-weighted average of 17.7 days of countywide smoke coverage per year. Drifting wildfire smoke plumes induce sharp air pollution shocks that typically last a few days and have magnitudes typical of daily variation in U.S. air quality. At the daily level, we estimate that exposing a county to an additional day of smoke increases concentrations of particulate matter smaller than 2.5 microns ($PM_{2.5}$) by an average of 2.2 $\mu g/m^3$, about one-third of the daily standard deviation.[2] At the annual level, we estimate that an additional day of smoke raises a county's annual average $PM_{2.5}$ concentration by 0.019 $\mu g/m^3$, about 0.9 percent of the annual standard deviation. Controlling flexibly for wind direction has little effect on these estimates, suggesting this variation in air quality is primarily due to wildfire smoke rather than other upwind sources.

Three primary results emerge from the analysis. First, we find that wildfire smoke exposure leads to statistically and economically significant losses in annual labor income. Specifically, each day of smoke exposure over the year causes a roughly linear reduction in labor income of 0.07 percent in the year of exposure.[3] Similar income losses in the year following exposure indicate lasting reductions in health or wages. Because smoke in the year of exposure typically occurs about halfway through the year, this implies a current-year impact that is about twice as large as the lagged impacts (as a fraction of post-exposure days). As a placebo test, we do not find a significant effect of smoke on income in years prior to the exposure. By analyzing annual income and allowing for lagged effects, our estimates capture medium- to long-run effects of transient pollution exposure. In contrast, shorter-run effects, which have been the focus of most prior studies of

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[2] Biomass burning may be more harmful to human health than car exhaust and most sources of industrial pollution, because it contains a higher share of volatile organic compounds (VOCs), a particularly harmful class of particulate matter. However, our mortality estimates are in line with previous effects estimated for particulate matter exposure, suggesting that wildfire smoke is comparable to other sources of pollution. We discuss this further in Section 1, and estimate the full range of EPA-monitored pollutant responses in Section 3.

[3] Our primary estimates exclude county-years where wildfires burned. The expected direct effect of wildfires on labor market outcomes is ambiguous. Wildfires may destroy businesses and reduce economic activity while burning, but firefighting and rebuilding may temporarily increase incomes. In robustness checks, our estimates of smoke effects are smaller but still detectable when we include counties experiencing wildfire burn.

air pollution and labor market effects, could either overstate pollution effects due to intertemporal substitution in work effort or could understate effects due to lasting effects of illness or labor market disruption. We calculate that 17.7 days of wildfire smoke (the annual average) reduces U.S. annual labor income by 1.26 percent, or $93 billion in 2018 dollars. Summing the smoke effects in the year of and year after exposure produces losses of 1.98 percent, or about $147 billion in 2018 dollars.

Second, we show that smoke affects employment, which can explain part of the persistent earnings effect. We estimate that an additional day of smoke exposure reduces employment by 302 per million individuals aged 16 and older, which is approximately a 0.046 percent reduction. Under reasonable assumptions, the effects associated with this extensive margin response can explain half of the overall decrease in income due to smoke exposure. Effects are largest among older workers, suggesting that poor health may amplify the negative labor market effects of air pollution.[4] We also find evidence that wildfire smoke exposure increases the receipt of Social Security income. To the best of our knowledge, these results provide the first evidence linking air pollution to extensive margin and retirement responses and indicate a channel through which short-run changes in air quality may have lasting impacts on the labor market.

Third, we find the labor market cost of wildfire smoke in the United States to be substantially higher than the mortality cost. Using a similar strategy as employed in our analysis of labor market effects, we find mortality responses are concentrated among individuals aged 60 and older and within six months of smoke exposure. Specifically, each day of exposure to smoke leads to 9.3 additional deaths per million residents. Using an approach that values each lost life year at $100,000, we estimate that premature mortality due to wildfire smoke imposes costs of $15.6 billion per year. Using a model of health and labor supply, we analyze the welfare implications of the $93 billion in lost labor market earnings each year due to wildfire smoke. Our approach indicates that the welfare cost of lost labor income is more than four times as high as mortality cost. These results

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[4]Medical and public health studies find that vulnerability to respiratory and circulatory illness rises with age, suggesting older workers may be particularly responsive to air pollution (e.g., Bentayeb et al., 2012; Schlenker and Walker, 2016). For examples of the mortality literature, see Dockery et al. (1993) and Pope et al. (2009). See Chan and Stevens (2001) for evidence related to job search at older ages.

contrast with previous estimates that find that the costs of premature death represent over 80 percent of the total welfare costs of air pollution.[5] In the absence of quasi-experimental variation, however, previous estimates of the aggregate labor market costs of air pollution have relied on strong assumptions in lieu of direct estimation.[6] Our results overcome this limitation and provide a comparison of mortality and labor market effects that arise from the same quasi-experimental variation in pollution exposure.

In addition to providing the first empirical evidence on the aggregate effects and relative importance of labor market channels in the evaluation of the costs of air pollution, our paper makes several other contributions to the literature. First, for pollution-abatement policy, the pollution variation we study consists primarily of variation in levels that do not exceed regulatory standards set by the Environmental Protection Agency. Nevertheless, our findings indicate that such pollution may significantly reduce labor market earnings. Failure to consider labor market costs may therefore lead to inefficient pollution standards and regulations. Second, our finding that reductions in air pollution can increase labor income through improvements in health or increased productivity indicates the possibility of a "double dividend": reducing air pollution to align the private marginal cost of abatement with social marginal benefits can improve population health and productivity and can also generate additional income tax revenue that could be used to lower tax rates and the distortions they impose (Williams III, 2003). The national representation of our estimated income effect from pollution reductions enhances the relevance of our estimates for evaluating the magnitude of revenue effects from other air pollution regulations.

Moreover, our findings shed light on how changes in health can lead to changes in employment, earnings, and retirement behavior. The propagation of short-run labor market shocks, especially those that generate job loss, are of long-standing interest in labor and macroeconomics (Jacobson,

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[5]See OECD (2016) for a summary of the literature. The World Bank (2016) estimates that labor market costs comprise less than 5 percent of the total welfare costs of air pollution worldwide and in North America. The U.S. Environmental Protection Agency (2011) estimates that 85 percent of the benefits of the Clean Air Act come from reductions in premature mortality.

[6]The EPA's usual method measures lost earnings by multiplying the dose-response function, estimated from medical records or taken from previous literature, and associated number of days lost due to a given illness, usually taken from survey evidence. For example, this method would involve gathering data on the increase in asthma attacks on smoky days, and then multiplying this by the number of days of work lost due to a typical asthma attack.

LaLonde and Sullivan, 1993; Neal, 1995; Jarosch, 2015). Our findings that pollution shocks translate into reductions in labor income and labor force participation add to a relatively small body of literature that documents the lasting impacts of changes in health on labor supply using quasi-experimental evidence (Coile, 2004; Stephens Jr and Toohey, 2018). We find significantly larger responses in urban areas, and larger point estimates in poorer areas with more black residents, suggesting that high rates of hourly work and narrow coverage under the Family Medical Leave Act may play a role in transmitting short-run shocks to lasting changes in income. In light of on-going population aging, the link between air pollution and premature retirement is of increasing policy relevance.

Finally, our research extends the growing body of literature on the economics and social costs of natural disasters to the study of wildfire. Like the economic losses caused by other natural disasters, the damage from wildfires can be mitigated or exacerbated by policy. Our findings suggest, however, that, unlike the losses caused by most other natural disasters, the damage from wildfire arises largely from externalities, as the costs may be concentrated in locations far from the fires themselves. These social costs should be considered alongside traditional considerations of damage to property, natural resources, and the costs of firefighting, and may significantly alter optimal policy in local land use and fire management.[7] Climate change has the potential to multiply the damage done by wildfires, as the National Research Council estimates that each degree Celsius increase in global temperature may lead to a quadrupling of acreage burned.[8] More broadly, these findings contribute to a growing body of literature on trans-boundary pollution with international implications, as an important share of wildfire smoke in the U.S. originates in Canada or Mexico (Lipscomb and Mobarak, 2016; Monogan, Konisky and Woods, 2017; Yang and Chou, 2017).

Section 1 provides background on wildfire and a model of the links between air pollution and

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[7]Kochi et al. (2010) surveys the literature, finding only six studies that have quantified the economic cost of wildfire smoke, and none that include economic costs manifested through the labor market.

[8]Climate change is projected to increase temperatures and reduce precipitation, leading to longer and more intense fire seasons; for example, every one-degree-Celsius increase in global temperature is projected to quadruple acreage burned by wildfires. See National Research Council (2011) for more details on this projection, and Moritz et al. (2012) for more on modeling of climate-and-wildfire linkages. Consistent with predictions generated by these models, recent fire seasons have set records in number of fires, acreage burned, and property damage.

labor market outcomes. Section 2 describes our data, and Section 3 explains our empirical strategy. Section 4 reports our main results on earnings, and labor force participation and retirement. Section 5 discusses the welfare costs of wildfire smoke exposure, with particular attention paid to the comparison of labor market impacts to mortality costs. Section 6 concludes.

1 Background and Conceptual Framework

How do transient air pollution events, such as wildfire smoke, affect labor market earnings? A well-developed body of literature in biomedical sciences, public health, and economics demonstrates negative effects of air pollution exposure on short-run performance and health outcomes.[9] Wildfire smoke, like other air pollution, contains particulate matter that enters the lungs and can pass into the bloodstream. This fine particulate matter carries with it numerous pollutants, such as ozone, carbon monoxide, atmospheric mercury, and a range of volatile organic compounds (VOCs). Exposure to these pollutants diminishes human health and performance. Inert particulate matter may also be harmful to human health. Health effects of exposure can have direct consequences on labor supply, leading to missed work days and reduced productivity. The EPA and other large research organizations have traditionally focused their research on concurrent hours responses lost due to illness. Although a growing body of literature documents productivity effects, we know of no estimates of the general incidence on workers.

While wildfire smoke is understood to operate through the same channels as other sources of pollution, the composition of wildfire smoke may make it more harmful to human health per unit of

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[9]The literature has made important progress in documenting the effects of air pollution on outcomes such as worker productivity, usually in narrow settings chosen to minimize the confounding effects of changes in economic activity. See Hanna and Oliva (2015) and Aragon, Miranda and Oliva (2016) for air pollution effects on hours worked; Hausman, Ostro and Wise (1984), Hansen and Selte (2000) and Holub, Hospido and Wagner (2016) for sick leave; Graff Zivin and Neidell (2012) and Chang et al. (2014) for the productivity of agricultural workers; He, Liu and Salvo (2018) and Adhvaryu, Kala and Nyshadham (2016) for the productivity of Chinese and Indian manufacturers, respectively; Chang et al. (2016) for the productivity of indoor call center workers; Lichter, Pestel and Sommer (2015) and Archsmith, Heyes and Saberian (2016) for the performance of soccer players and baseball umpires, respectively; Ebenstein, Lavy and Roth (2016) and Roth (2016) for test score performance. See Graff Zivin and Neidell (2009) and Aldy and Bind (2014) for effects on demand for goods and services, such as for entertainment, hospitality and tourism.

measured particulate matter than most industrial sources of pollution.[10] The most comprehensive evidence pertaining to the effects of wildfire smoke exposure on health in the United States comes from Miller, Molitor and Zou (2017), who use national-scale variation in daily smoke exposure to document a link between smoke exposure and adult mortality and morbidity. Using conventional figures for the value of a statistical life-year, they find that the mortality cost of wildfire smoke is significantly higher than the hospital-related morbidity cost as captured by health care spending. Other case studies of wildfire smoke anomalies have also found suggestive evidence that the mortality cost of wildfire smoke exceeds the morbidity cost (e.g. Kochi et al., 2012, 2016). Another strand of research documents costs to infant health, which may have large valuations attached to them in cases of long-lasting damage (Jayachandran, 2009; McCoy and Zhao, 2016).

In addition to direct health effects, it is increasingly recognized that behavioral responses to air pollution pose a deep challenge to translating currently available estimates of the effects of air pollutants to policy-relevant parameters. Graff Zivin and Neidell (2013) survey the literature on avoidance behavior and discuss the challenges it presents for estimating the effects of air pollution.[11] For wildfire smoke in particular, survey research has documented a number of margins of behavioral responses to wildfire smoke, such as spending more time indoors, running air conditioners for longer times, and missing work (Richardson, Champ and Loomis, 2012; Jones et al., 2015). Richardson, Champ and Loomis (2012), examining a single large wildfire in California in 2009, estimate that the economic costs of health effects are comprised primarily of avoidance, defensive actions, and disutility, with only about 10 percent of costs due to illness.

The previous literature suggests that labor market effects may arise from health effects and avoidance during and immediately after air pollution events. More significant losses may occur if these short-run effects catalyze longer-run labor market responses, yet little is known about the

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[10]Research on the differences in the composition of smoke from biomass burning and car exhaust find higher reactivity of VOCs in smoke, which is consistent with the incomplete burning of the carbon material in a fire relative to internal combustion (e.g., Verma et al., 2009, 2015; Bates et al., 2015). Wildfire is noteworthy for containing a more noxious mix of chemicals and higher levels of extremely fine particulate matter than most biomass burns Liu et al. 2017.

[11]For examples of the literature on air pollution and avoidance behavior, see Chay and Greenstone (2005) for long-run responses, including residential sorting, and Moretti and Neidell (2011) for short-run avoidance behavior.

long-run effects of transient air pollution shocks in adulthood on either health or labor markets. Theoretically, short-run health effects of air pollution may result in lasting earnings losses over a longer time period through either health channels or interactions with the labor market. Biomedical mechanisms exist through which short-run exposure may affect medium- and long-run health. Most directly, once particulate matter enters the body, it may take weeks or months for it to be cleared. In addition, transient exposure may result in adverse health events, such as heart attacks or the onset of asthma, reducing health capital and leaving exposed individuals more vulnerable to future health shocks. For example, exposure to adverse economic and environmental conditions in early childhood has been found to lower educational attainment and earnings later in life (Case, Lubotsky and Paxson, 2002; Isen, Rossin-Slater and Walker, 2017). Temporary labor market disruptions can also have lasting impacts on earnings and welfare, as shown in numerous studies of displaced workers and labor market entrants (Jacobson, LaLonde and Sullivan, 1993; Kahn, 2010; Oreopoulos et al., 2012; Borgschulte and Martorell, 2017). Workers in the United States have varying and often weak job protections when they or family members fall ill.[12] Wages may respond to more serious illnesses due to lasting changes in workers' productivity or employment. We know of no evidence on the effects of such responses to air pollution; however, their importance has been demonstrated in other contexts. For example, lower wages resulting from a health shock is the primary source of earnings losses following hospitalization (Dobkin et al., 2016).

To illustrate the multiple channels of action implied by the combination of direct health effects, behavioral responses, and long-run wage effects, we build a simple model of health and labor supply to connect exposure to airborne pollutants with labor market earnings, our primary outcome measure. We model the utility of a representative agent in response to a fixed dose-response function, $s(c)$, relating exposure to pollution concentration, c, to sick days, $s(c)$. Pollution concentration may represent a vector of harmful components in wildfire smoke. An agent maximizes

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[12]The Family Medical Leave Act covered 59% of workers in 2012, and allowed them to take up to 12 weeks of unpaid leave for their own serious health condition, or that of a spouse, parent, or child (Klerman, Daley and Pozniak, 2012).

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utility that depends on consumption, X, leisure, l, sick days, s, and exposure, c:

$$\mathbf{max}_{X,l} U(X,l,s,c)$$

$$\text{s.t. } Y + wh \geq X$$

$$l = T - s - h$$

Consumption will equal non-labor income, Y, and earnings, wh. Wages respond to pollution, $w = w(c)$, due to a combination of responses through three channels: changes in the returns to work arising from a decay in human capital after an illness, the incidence on workers of labor demand changes, and direct productivity effects during periods of high pollution. T reflects the total time endowment, from which days of illness, $s(c)$, are directly subtracted. Hours of work, $h = h(w(c),c)$, respond to wages and direct avoidance of high pollution.

The resulting earnings function is:

$$E(c) = w(c) \cdot h(w(c), s(c), c) \tag{1}$$

Taking derivatives and re-arranging yields a decomposition of the reduced-form effect:

$$\frac{dE(c)}{dc} = w\left[\frac{\partial h}{\partial s}\frac{ds}{dc} + \frac{\partial h}{\partial c}\right] + h\left[\frac{dw}{dc}\right](1 + \eta_s) \tag{2}$$

The first bracketed term in Equation (2) captures the direct effects of pollution on labor supply. The first term inside the brackets, $\frac{\partial h}{\partial s}\frac{ds}{dc}$, denotes the loss of hours of work to illness, and the second term, $\frac{\partial h}{\partial c}$, reflects avoidance behavior. The second bracketed term, $\frac{dw}{dc}$, captures the effect of pollution on wages. The final term, $(1 + \eta_s)$, scales the endogenous labor supply response to changes in the wage; as wages fall with pollution exposure, workers may reduce their hours of work. Thus, we expect the effect of air pollution on earnings to be the sum of the effects working through the direct effect on hours, and the combined effects on wages and endogenous labor supply response.

The primary focus of the paper is on estimating $\frac{dE(c)}{dc}$, the total response of earnings to variation

in air quality. We also examine evidence for the components of the losses, especially the response of hours through a labor force participation channel. Following our main estimates, we return in Section 5 to Equation 2 to guide our analysis of the welfare effects of the lost earnings.

2   Data

Our analysis relies on a novel, nationwide linkage of wildfire smoke exposure, air pollution, weather conditions, labor market outcomes, and mortality. These data sources include a rich set of remote sensing, environmental monitoring, federal income statistics, national representative surveys, and death records data files. This section describes the construction of the database and the definitions of our key variables used in the analysis.

2.1   Wildfire Smoke Data

A key innovation of this analysis is that we are able to observe labor market outcomes linked to annual counts of wildfire smoke exposure at a fine geographic level over a broad geographic scope. These daily smoke exposure data were originally developed by Miller, Molitor and Zou (2017) using wildfire smoke analysis produced by the National Oceanic and Atmospheric Administration's (NOAA) Hazard Mapping System (HMS). The HMS is a program that utilizes a variety of satellite and spacecraft observations to identify fire and smoke emissions over the contiguous United States (Ruminski et al., 2006). An important output of the HMS is the daily geo-referenced smoke plume files, drawn manually by smoke analysts, that represent the outlines of smoke plumes emitted by wildfires. We obtain digital archives of the daily plume files from 2006 to 2015 and construct our key smoke-exposure variable separately at the county level. To construct our measure of wildfire smoke exposure, we first code the fraction of county that is covered by any smoke plume detected by the HMS on that day.[13] We then code a county as exposed to smoke if it is on the interior of

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[13]In producing smoke plume outlines, the HMS uses data from the Geostationary Operational Environmental Satellite (GOES) visible band imagery available at the 1 km resolution and infrared bands at the 2 km resolution. The granular resolution enables us to explore geographically fine variations in exposure at the county level.

the plume. The results are qualitatively similar, but slightly smaller magnitude, when we measure exposure using partial coverage with a smoke plume.

We complement satellite smoke observations with wildfire records from the National Fire and Aviation Management group of the U.S. Forest Service, which combines records from seven major fire and wildland management agencies.[14] We use these data primarily to distinguish areas directly affected by the burning of fires.

2.2   Pollution Data

We link satellite smoke observations with ambient air pollution monitoring data obtained from the U.S. Environmental Protection Agency's (EPA) Air Quality System (AQS). We extract monitor-daily readings for EPA "criteria pollutants," including fine particulate matters ($PM_{2.5}$), coarse particulate matter (PM_{10}), ozone (O_3), carbon monoxide (CO), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2). We focus on these pollutants because their concentrations are expected to elevate during wildfire events and they are recognized by the EPA to be among the most important pollutants that affect human health.

To measure air pollution at the local level, for each pollutant we take the weighted average of all readings from monitors that fall within 20 miles of a county's centroid, where the weights used are inverse monitor-to-centroid distance. Depending on the sparsity of the monitoring network, a significant number of areas have no pollution monitors within a 20-mile radius and therefore are missing pollution data. Pollution readings can differ by pollutant, as well: 1,642 counties have O_3 data, while we are able to obtain NO_2 observations for only 691 counties.[15]

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[14]These include the Bureau of Indian Affairs, the Bureau of Land Management, the Bureau of Reclamation, the California Department of Forestry and Fire Protection, the National Park Service Fire and Aviation Management, the U.S. Fish & Wildlife Service, and the U.S. Forest Service.

[15]Areas and days with missing data are mostly due to the U.S. EPA's goal of cost-effectively monitoring urban air quality. For example, the 1,300 counties among which we can measure $PM_{2.5}$ capture about 70 percent of the U.S. population and are mostly urban areas. In areas with monitoring systems, data can be missing on some days due to intermittent monitoring schedules and, occasionally, equipment failure. The 20-mile inverse distance weighting is intended to maximize the usage of available data and interpolate pollution readings within a reasonable distance range. We do not otherwise interpolate or fill in missing pollution readings.

2.3 Weather Data

The analysis includes a flexible set of control variables for temperature, precipitation, and wind patterns. Temperature and precipitation data are collected from the National Climatic Data Center's Global Historical Climatology Network (GHCN), which provides station-daily-level information on minimum temperature, maximum temperature, and total precipitation. To construct weather conditions at the local level, we average daily weather readings from stations that fall within 20 miles of each county's centroid, weighting readings by inverse station-to-centroid distance.

We obtain wind speed and wind direction data from the National Centers for Environmental Information's North American Regional Reanalysis (NARR). NARR divides the United States into 32km×32km grids, and for each grid-day it provides data on the East-West wind vector ("u-wind") and the North-South wind vector ("v-wind"), which together characterize windspeed and direction. Given the resolution of the data, we construct wind conditions at the county level by first linearly interpolating u-wind and v-wind vectors at the grid centroids to the county centroid, and then converting u-wind and v-wind at the county centroid into wind speed and wind direction.

2.4 Earnings Data

Our main earnings analysis uses outcome data from four sources: the Quarterly Workforce Indicators (QWI), the County Business Patterns (CBP), the Regional Economic Information System (REIS), and the Internal Revenue Service's (IRS) Individual Income Tax Statistics. While all four earnings sources approach full coverage of labor earnings in the United States, each source has a distinct construction. For example, the IRS data, which are based on stratified probability samples of individual income tax returns as reported on Forms 1040, 1040A, and 1040EZ, will include only workers who file tax returns by the end of the calendar year that follows the year of tax liability; of course, under- and mis-reporting may occur in these data.[16] CBP, which is based on the Census Bureau's Business Register, excludes data on self-employed individuals, employees of private households, railroad employees, agricultural production employees, and most government

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[16]<https://www.irs.gov/pub/irs-soi/sampling.pdf>

employees, whereas REIS includes these workers.[17] QWI, on the other hand, excludes members of the armed forces, self-employed individuals, proprietors, and railroad employees. By using four distinct data sources, we can replicate the main findings and demonstrate robustness to the construction of aggregate labor income.

2.5 Labor Force Status and Social Security Data

We draw county-level labor force participation information from two sources. First, we use Local Area Unemployment Statistics (LAUS) published by the Bureau of Labor Statistics. LAUS contains county-level labor force estimates produced through a building-block approach that combines data from national representative surveys and state unemployment insurance systems.[18] Second, We use the Quarterly Workforce Indicators (QWI) published by the Census Bureau to measure employment jobs both at the county aggregate and by age groups. We measure number of retirement claimants and benefits at the county level using the Social Security Administration's (SSA) annual publications of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries statistics. The SSA produces these statistics using its Master Beneficiary Record, which covers the universe of Social Security beneficiaries who are ever entitled to receive retirement and survivors insurance or disability insurance benefits. For each county-year, we observe retirement benefits paid out to claimants in that county. In addition to the SSA data, we also make use of the "retirement and disability insurance benefits" field available in the county-level REIS data.

2.6 Mortality Data

Mortality outcomes are measured in micro-data provided by the National Vital Statistics System. The underlying data are taken from death certificates which contain age of death. We use the

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[17]CBP's payroll and employment information are derived from administrative records for the universe of firms. CBP's payroll measure is based exclusively on administrative records for single-unit companies. For multi-unit companies, CBP's payroll information comes from a combination of administrative records with Census data. See <http://www.census.gov/econ/cbp/methodology.htm>.

[18]LAUS county level estimates use survey data from the Current Population Survey, the Current Employment Statistics survey, and the American Community Survey (ACS). See <http://www.bls.gov/lau/lauov.htm>.

restricted data files containing month of death and all counties in the United States to link mortality outcomes to smoke exposure. The data are available for the entire sample period, 2006-2015, and contains 25.2 million deaths.

3 Empirical Framework

Researchers who study the labor market effects of environmental hazards face three primary challenges when seeking to identify the causal effects of air pollution on labor markets. First, observational correlations between air pollution and economic activity may be due in part to the causal effects of the economic activity on air pollution. As a result, finding a valid instrument for air pollution that does not have a direct effect on labor markets is difficult. For example, policy instruments which reduce air pollution may impose direct effects on the regulated markets. Second, transient changes in air pollution may induce short-run effects that reflect intertemporal substitution, rather than true welfare-reducing labor market effects. Third, existing evidence of a relationship between pollution and labor markets has generally focused on case studies of specific industries or regions. These specific settings may not produce nationally representative effects and may not generate sufficient variation to study relatively rare but significant outcomes, such as retirement or mortality.

3.1 Wildfire Smoke Exposure

We use annual variation in regional wildfire smoke exposure to identify the causal effects of transient air pollution shocks on labor markets. A few key features of wildfire smoke permit a research design that addresses the identification challenges described above.

First, wildfire smoke plumes are a natural source of air pollution, traveling hundreds or even thousands of miles downwind, affecting cities at great distances from the fire itself. Figure 1 provides summary statistics for the frequency of the events. On a population-weighted average, counties are fully covered by smoke plumes for 17.7 days per year.[19] Smoke exposure is con-

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[19]Appendix Figure A.1 depicts an example of smoke exposure across much of North America during the Fort McMurray fires in northern Canada. Fires in the U.S. Southeast also appear in the figure.

centrated in the upper Midwest but exhibits significant year-to-year variation. Importantly for a study focused on air pollution, the pattern of smoke exposure differs markedly from wildfire footprints (see Appendix Figure A.2). Thus, we can study the effects of downwind smoke exposure separately from direct damages caused by occurrences of wildfires. Our primary analyses exclude county-years experiences wildfire burn.

Second, smoke shocks give rise to spikes in air pollution concentration, with the average magnitude large enough for us to expect significant health and behavioral responses. The upper panel of Table 1 shows that wildfire smoke increases concentrations of the six EPA criteria pollutants we examine, with the largest responses in particulate matter and ozone. An average smoky day increases $PM_{2.5}$ by 2.2 $\mu g/m^3$ on the day of exposure, about one-third of a standard deviation in the distribution of daily particulate matter. When we examine the cumulative effect of smoke days on annual pollution measures in the lower panel of Table 1, we estimate that increasing smoke exposure by one day increases the annual $PM_{2.5}$ by 0.019 $\mu g/m^3$; evaluated at the annual average number of smoke days (17.7), smoke raises a county's annual average $PM_{2.5}$ concentration by 0.336 $\mu g/m^3$, or about 16 percent of the annual standard deviation. This implies that each day of smoke exposure contributes 6.92 $\mu g/m^3$ to the annual sum of daily $PM_{2.5}$ concentrations. This annual concentration effect of one day of smoke exposure is over three times as large as the same-day effect, implying that particulate matter lingers in the air, increasing pollution levels on days that are not coded as smoke exposure days in the satellite data.

Third, most wildfire smoke events induce modest, but largely humanly imperceptible, changes in air quality, meaning that our estimates are not driven by a small number of intense smoke exposure days. A potential concern with using wildfire smoke is that extreme wildfire smoke events generate substantial news coverage, possibly triggering behavioral responses that would not be present with normal sources of air pollution. The vast majority of smoke exposure days in our data lie within the normally experienced levels of air quality, helping to allay this concern. Additional evidence on the clustering of smoke days appears in Figure 2, which depicts an event study with $PM_{2.5}$ as the outcome variable and time since a smoke day as the event time. Smoke

15

days are associated with elevated levels of fine particulate matter for four days, with an average increase of just over 2 $\mu g/m^3$ on the day of exposure off an average of 10.3 $\mu g/m^3$ (see Table 1). To put this into context, the EPA long-run standard for $PM_{2.5}$ is 15 $\mu g/m^3$, while the daily $PM_{2.5}$ standard is 35 $\mu g/m^3$, far above most exposure levels. Thus, although wildfire smoke is a unique source of pollution, it seems plausible that behavioral responses to smoke—especially far from the fires themselves–will be similar to other fluctuations in air quality. Further details on the distribution of air quality appear in the Appendix.

Finally, we note that wind patterns that carry wildfire smoke to a region may also bring in pollution from other sources. If so, our research design can still be used to capture causal labor market effects of pollution shocks, but part of the effect we find could be the effect of upwind pollutant sources other than wildfires. To determine the role of wildfire smoke versus other pollution sources, we examine directly the extent to which wind patterns can explain our wildfire smoke effects. First, motivated by the research design in Deryugina et al. (2019), Appendix Figure A.3 reports daily first stage estimates of the pollution effect of wildfire smoke plume coverage with and without state- or county-specific current and lagged wind direction (60-arc degree) bins. The smoke effect estimates change little across specifications. Similarly, Appendix Table A.5 reports that annual first stage and reduced form point estimates change very little and actually become more precise when we control for state-specific annual wind patterns (this specification lacks the degrees of freedom for county-specific wind controls). We find these results to provide evidence in favor of interpreting our pollution effects as driven by wildfire smoke plumes, rather than by generically dirty wind patterns.

3.2   Identifying the Effect of Smoke Exposure on Labor Market Outcomes

Our identification exploits variation in the annual, cumulative number of wildfire smoke days at the county level to identify the labor market effects of smoke exposure. We identify over 720,000 county-day smoke exposure events from 2006 through 2015, and we aggregate to the annual level to construct $SmokeDays_{ct}$, the number of days in year t to which county c was exposed to wildfire

16

smoke. We then estimate the following regression equation:

$$Y_{ct} = \beta \cdot SmokeDays_{ct} + State_c \times Year_t + \alpha_c + X_{ct}\gamma + \varepsilon_{ct} \tag{3}$$

where Y_{ct} denotes labor market outcomes such as the log of per capita earnings in county c and year t. The primary coefficient of interest, β, can be interpreted as the effect of an additional day of wildfire smoke on annual earnings in the exposed county. We include county fixed effects, α_c, to control for time-invariant differences in county labor market outcomes. Our smoke exposure effects are therefore identified using year-over-year variation in smoke exposure within the same county. In addition, we control for state-by-year effects to capture time-varying changes at the state level, such as the Great Recession.[20] X_{ct} includes time-varying weather controls that may independently affect labor market outcomes. These include the summed exposure to various levels of heat (10-degree Fahrenheit bins of daily temperature), rain (quadratic annual precipitation), and wind (60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed). To reflect the smoke-exposure effect on a representative resident, we weight the regressions by county-annual population. To adjust for both within-county and state-year autocorrelation, we two-way cluster standard errors at the county and the state-by-year levels.

4 Results

4.1 Annual Earnings

Table 2 presents results from the estimation of Equation 3 where the outcome is the log of per capita labor income at the county level. We use earnings as measured by four distinct data sources, as well as a simple average of the four separate earnings measures. The results reported in the main text drop counties that experienced wildfires in the same year.

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[20]In the raw data, each additional day of smoke exposure in a county in a year is associated with 0.65 additional days of smoke exposure in the following year. Including county fixed effects, state-by-year fixed effects, and weather controls reduces this association to 0.07 additional days of smoke. Thus, conditional on these controls, there is little year-over-year serial correlation in wildfire smoke exposure.

Starting in column 1, we find that each day of wildfire smoke exposure in a county reduces average annual wage and salary earnings reported in the QWI by 0.059 percent. Across the four measures of annual labor income, exposure to wildfire smoke significantly lowers the average annual income in a county by between 0.054 and 0.080 percent. We cannot reject the equality of the estimates from the four data sources. We report the average income estimates in the remaining columns, and also add one lead and various lags of smoke exposure; we lose one year of data with the addition of each lead or lag, somewhat reducing the statistical power of the analysis. The effect across the average of the four income measures is 0.071 percent, as reported in column 5. When we add the first lead and the first lag of smoke exposure as shown in column 6, we find effects of 0.069 percent in the preceding year, and effects of 0.043 percent in the year of exposure. When comparing these magnitudes, it is important to note that most smoke occurs in the second half of the year. The average smoke day occurs in mid-July, day 196 of the year, meaning that we should multiply the year-of effects by 2.1 when comparing them with effects in the following years; we report the raw numbers in tables and figures, but this interpretation can be applied throughout the paper. In this case, earnings drop by 0.090 percent in the remainder of the year of exposure, consistent with a larger effect in the immediate period following the smoky day. The sum of smoke exposure in the year before and the year of income measurement is a 0.112 percent reduction in earnings with a standard error of 0.035; summing over the year of and two years preceding income measurement gives an estimate of 0.106 percent reduction in earnings with standard error of 0.041. Multiplied by the average number of smoke days in the sample period, these estimates imply a total loss of just under 2 percent of national labor income in the United States each year as a consequence of wildfire smoke. Total losses in 2018 dollars are $147.2 billion using one lag, and $139.3 billion using two lags.[21]

The linear fit can be visually assessed in the residual plot in Figure 3. The figure reports a binned scatter plot of the average income residual in ten equally-sized bins of smoke exposure. The fit line represents our main estimate in column 5 of Table 2. Most of the residuals fall close to

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[21]The calculation uses $6.4 trillion as total wage and salary compensation in 2010, as reported by the Bureau of Economic Analysis, and the Consumer Price Index to translate losses in 2018 dollars.

the regression line, and the results do not appear to be driven by extreme smoke exposure events. As suggested by this figure, in unreported analysis, we find that higher-order terms in exposure are not significant.

We perform several additional analyses and robustness checks, with detailed results reported in the Appendix. First, we test whether smoke exposure affects migration in and out of a county. We measure net migration flows (i.e. population size) using the total number of tax exemptions claimed in an area using IRS data. We also directly measure in- and out-migration using IRS county-to-county flows. The results, reported in Appendix Table A.1, indicate that population migration does not respond to smoke exposure to an economically or statistically significant degree. If anything, the insignificant point estimates indicate small *positive* effects of smoke exposure on the total population, and near-zero coefficients on both inflows and outflows. The lack of population migration response to smoke exposure suggests that our main effects are not an artifact of changes in population composition across regions. Next, we explore how the average smoke exposure effects reported in Table 2 vary by the intensity of smoke exposure. While our satellite measure of exposure captures the number of days of complete coverage in smoke, we could have used alternative measures based on partial coverage. We report the results of two alternative specifications in Appendix Table A.2, showing that similar results hold when we use the sum of (possibly) partial coverage or adopt a binary indicator based on greater than 75 percent (the average coverage conditional on *any* coverage) of the county covered in smoke. As a final robustness check, we examine robustness to alternative clustering choices for the calculation of the standard errors. Appendix Table A.4 shows that the choice to cluster at the county and state-by-year level has almost no effect on inference.

4.2 Extensive Margin and Retirement Behavior

An important and unanswered question in the literature on the labor market effects of air pollution is whether transitory air pollution episodes leave lasting impacts on labor markets. Two channels are suggested by the model in Section 1. First, air pollution may cause health events, such as

19

asthma episodes or heart attacks, which lead to chronic health conditions. These chronic conditions may reduce workers' productivity and labor supply, in extreme cases, causing them to leave the labor force altogether. Second, diminished health, whether temporary or chronic, may affect labor market opportunities. An extensive literature in labor economics documents the lasting effects of job loss, suggesting that particularly large losses may occur with changes in extensive margin labor force attachment. Further, because the health of older workers may be more sensitive to pollution shocks, we hypothesize that smoke effects should be strongest among older workers, potentially generating losses associated with labor market transitions and retirements.

We test for effects on employment in the following ways. First, we test for labor force participation (LFP) responses in the LAU data. Column 1 of Table 3 shows the results when we use employment as the outcome in Equation 3, including a lead and a lag in smoke. Results suggest that each day of wildfire smoke reduces LFP in the county by 147 per million aged 16 and over.[22] Second, we use the Census Bureau's Quarterly Workforce Indicators (QWI) to test explicitly for employment responses in total employment to smoke exposure. Column 2 contains results for all workers, and shows a drop of 289 employees per million residents. Off an average employment rate of 63 percent, this implies that each day of exposure reduces employment by 0.046 percent.

In column 3 we focus on workers above age 55, and find a decline in employment of 177 employees per million residents.[23] Reduction in employment of older workers may reflect retirements, and for this reason, we next examine retirement-related outcomes, such as Social Security retirement benefit claiming, using data from the REIS and the Social Security Administration (SSA). For the REIS analysis, we examine total payments of retirement and disability benefits in the same framework as in the primary earnings analysis, finding a 0.026 percent increase in benefit payments for each day of exposure, as seen in column 4. In the SSA analysis, we use the same specifications as above applied to data derived from SSA's administrative records. Table 3 contains results for SSA benefits per capita (column 5). Importantly, the SSA data are annual, so retirements must be

[22]The unit is employment per million population aged 16 and over. Specifically, we divide county employment by the county's population aged 16 and over, and then we multiply the number by 1,000,000 for readability.

[23]In Appendix Figure A.4, we report the age-profile of response in the QWI. The largest responses are in the ages 55 to 64, and 65 and over.

shifted significantly to be captured by this measure. We present the results of testing for a change in Security benefits paid, finding that the benefit per claimant rises 0.015 percent per day of smoke exposure. Comparing this result with the preceding estimates, we estimate that a share of the change in participation and employment may be associated with new Social Security claimants.[24] In all cases, we can interpret the increase in per beneficiary payments as evidence of increased need for financial resources among the elderly population.

A significant portion of the earnings results can be explained by the extensive margin effects. If those who leave the labor force earn average incomes and the reduction in labor supply lasts one year, the average annual exposure of 17.7 days implies a 0.81 percent reduction in earnings. Comparing this to the total effect of 1.26 percent reduction in earnings, implies that more than half of the earnings effect could be explained by extensive margin responses. This calculation illustrates the potential for relatively small but recurring shocks to employment to have large effects on total earnings. It is also important to note that we lack the power to examine how movements in and out of the labor force impact wages, an important channel in the job loss literature.

4.3 Heterogeneity by County Characteristics and Industry

With our national variation, we can perform heterogeneity analyses that has not been possible to conduct in previous studies of air pollution and labor markets. Patterns in heterogeneity may provide suggestive evidence of underlying mechanisms behind the earnings and employment losses. To maintain consistency with our previous analysis, we examine how county-level characteristics predict the size of earnings losses. We split the sample into above- and below- median values of a number of characteristics: fraction that is urban, fraction in poverty, median home value, fraction that is black, and average smoke days. We then re-run the earnings models with interactions between smoke exposure and indicators for the characteristics.

In Table 4 we report the results of the earnings heterogeneity analysis. We base the analysis

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[24]The Social Security rules do not require claimants to quit work to claim benefits, and it is possible that some claimants do not show up as labor force dropouts.

off of the dynamic specification shown in column 6 of Table 2, and we focus on the interaction between the current year smoke effect and county-level characteristics. In the first column, we find that counties with above average urban fractions explain the majority of the earnings losses we find, with a 0.049 percent reduction in labor income, while in areas with below average fraction urban, there is no detectable effect. We test whether we can reject the equality of these coefficients, finding a p-values less than 0.01 . In this case, we strongly reject the equality of the effect in more- and less-urban areas, and conclude that responses are concentrated in urban areas. This finding is important for excluding a direct effect of fires as a primary mechanism behind the earnings losses. Effects are also concentrated in high home-value areas, consistent with the urban-rural heterogeneity. Continuing across the columns, we report that we find larger earnings losses in areas with higher poverty rates and higher fraction black, though we cannot reject the equality of the coefficients in both cases very precisely (p-values > 0.06). In the last column, we stratify counties based on county's 10-year (2006-2015) average $PM_{2.5}$ concentration. One possibility is that that high pollution areas may have more fully adapted to exposure, which could be reflected in a lower responsiveness to smoke. The evidence suggests, however, that there is no significant heterogeneity across high vs. low pollution areas.

We also conducted additional analyses of heterogeneity by industry with results reported in Figure 4. The industry analysis is conducted using the QWI data, which identifies earnings at the industry level. Point estimates are generally insignificant, but suggest that smoke has stronger effects in the mining, real estate, and construction industries; weighted by industry size, the largest losses are in manufacturing, professional services, and construction. We find a relatively sharp zero in agriculture, in spite of previous evidence of reduced worker productivity in previous studies. Note, however, that the agriculture sector is rather broadly defined in our study and includes sectors such as crop and animal production, logging, fishing, etc. As we discuss in Section 4.3, an advantage of studying annual outcomes is that the estimates are net of daily fluctuations that are due to short-run intertemporal substitution.

5 Welfare

5.1 Air Pollution and Welfare

In the preceding sections we have demonstrated earnings losses and changes in labor force partici-
pation as a result of wildfire smoke exposure. Of course, the earnings response does not necessarily
reflect individual or social welfare responses, which depend on the mechanisms that explain the
decreased earnings. In particular, at least some portion of the lost earnings may be explained by
increased leisure, for example, if workers stay home on high-pollution days. Similarly, if some
workers are forced into early retirement by smoke-related illness, we would like to account for
the replacement of market work with home production. Optimal policy should weigh the marginal
cost of reduced pollution against the marginal damage to social welfare.

5.1.1 The Double Dividend through Increased Labor Income

Studies in public and environmental economics consider how air pollution regulation interacts with
the tax-distorted labor markets. While taxes on pollution may or may not generate any benefits in
the labor market (Goulder, 1995; Fullerton and Metcalf, 2001), pollution regulations that improve
labor incomes through health and productivity channels are shown to produce a "double dividend"
(Schwartz and Repetto, 2000; Williams III, 2002, 2003). This second source of welfare gains arises
because increases in labor supply alleviate pre-existing tax distortions associated with payroll,
income, and sales taxes.

Calibrating the changes in welfare through this channel is straightforward in partial equilib-
rium. On the margin, increases in labor supply will reduce deadweight loss by an amount that
equals the change in labor times the average marginal tax rate for affected individuals. While we
do not have a direct measure of this tax rate, we can use a moderate value of 25% to calculate that
welfare increases by one-quarter of the $93 billion total loss, or $23 billion. This is a conservative
lower bound on the total welfare loss, as it does not consider the effects of changes in individual
welfare through either increased post-tax income or utility gained from health and amenities.

5.1.2 Individual and Social Welfare

For individual welfare, we can perform a simple calculation building off the models in Section 1 and Dobkin et al. (2016), and estimates reported in Table 2. To focus attention on the labor market costs, we separate workers' losses that occur through consumption and leisure, x and l, from direct losses arising from changes in health and amenities, s and c. We label utility from the first two terms as $U^{LM}(x, l)$; normalizing by the marginal utility of consumption gives the labor market component of welfare, W^{LM}. In the next subsection, we return to the issue of costs arising from illness. We also simplify the model by dropping avoidance behavior, and focusing on long-run effects, motivated by the persistent losses we find in the earnings analysis. Individual welfare losses arise from reductions in the wage, endogenous labor supply responses, and reductions in the time endowment due to illness. Social welfare losses include these changes in addition to changes in deadweight loss, i.e. the double dividend channel.

Considering a small change in pollution concentration, c, the loss in money-metric utility to the worker is

$$\frac{dW^{LM}}{dc} \equiv \frac{dU^{LM}/dc}{MU_x} = h\frac{dw}{dc} - w\frac{ds}{dc}.$$

The first term relates to the change in the wage, which leads to a welfare loss in proportion to labor supply, h. Intuitively, a lower wage directly subtracts dollars from consumption; then, hours change in response to reflect a re-optimization at this lower utility frontier. The second term reflects the direct loss of time due to illness, valued at the wage. We can then take the ratio of the above individual welfare loss to the lost earnings in order to calibrate the appropriate scaling of the earnings losses.

Absent detailed data on time use and illness, we require some assumptions to calibrate the percentage of share of earnings losses that reflect true welfare costs to individuals. We focus on the case where all responses arise from changes in the wage, as in Dobkin et al. (2016), but also consider changes in the time endowment to provide an informative upper bound. Specifically, individual welfare losses as a share of earnings losses lie between the wage response, $\frac{1}{1+\eta_{h,w}}$, and

an upper bound of unity, the case when all earnings losses reflect time spent sick. Should welfare costs arise entirely due to changes in the wage, we can take a conservative value of the labor supply elasticity, $\eta_{h,w} = 0.5$ (drawing from Keane (2011), as in Dobkin et al. (2016)), to estimate that two-thirds of the earnings loss reflect true costs to the worker.

Moving from individual to social welfare involves considering both individual welfare losses and changes in deadweight loss from taxation. In the case where earnings losses arise from responses to the wage, social welfare losses are the sum of individual losses and the deadweight loss of the labor supply response due to taxation, which can be calculated by multiplying the marginal tax rate by the difference between earnings responses and the individual welfare loss.[25] Assuming a marginal tax rate of 25% and $\eta_{h,w} = 0.5$ implies a social welfare effect of 75% (two-thirds from labor supply plus one-twelfth from deadweight loss) of lost earnings.

Applying the above model to the estimates reported in Table 2, we find that the welfare losses working through labor market responses are $70 billion in 2010 dollars. The lasting damage to labor market opportunities show up as lower wages, but may reflect either reduced health capital following an acute smoke-induced illness (i.e. lower productivity of workers following the health shock), or worker transitions to lower-paid jobs induced by illness or labor-demand effects. Losses may approach an upper bound of $93 billion, if responses occur entirely through perfectly inelastic responses, as when workers are constrained from working by illness. Alternatively, at a lower bound where all lost income arises from perfectly elastic labor-supply responses, social welfare falls by 25% of lost earnings, or $23 billion. We regard this scenario as unrealistic; it is informative primarily because it generates important welfare responses entirely through the double dividend channel, and applies under the most pessimistic model of individual behavior. Costs associated with mortality, health care expenditures, the disutility of smoke-induced illness, and other costs would then be added to this figure to reach the total damage done by wildfire smoke.

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[25]Intuitively, lost earnings that arise from labor supply response are replaced by leisure in the individual's utility. However, this leisure is subsidized by the government at the marginal tax rate, leading to deadweight loss.

5.2 Comparison with Mortality Costs

To evaluate the importance of incorporating labor market effects into estimates of air pollution costs, we benchmark the welfare cost of lost earnings against that of premature deaths due to smoke exposure. We focus on estimation of the mortality effect at the monthly level, the finest temporal frequency at which we can measure mortality rate, although in some specifications below we also estimate effects at longer horizons. Our mortality regression specification closely mirrors Equation 3 from our earnings analysis. We regress the mortality rate M_{cmy} in county, c, month of the year, m, and year, y, on the number of days, $SmokeDays_{cmy}$, in which the county was exposed to wildfire smoke that month:

$$M_{cmy} = \beta \cdot SmokeDays_{cmy} + State_c \times Year_y + County_c \times Month_m + X_{cmy}\gamma + \varepsilon_{cmy}. \qquad (4)$$

The primary coefficient of interest is β, which describes the effect of an additional day of smoke exposure on mortality. We measure mortality as deaths per million in the month of smoke exposure. To account for delayed mortality effects as well as possible short-run mortality displacement (harvesting), we also estimate specifications where mortality is measured over 3-, 6-month, and 12-month windows beginning with the month of exposure. We include the same weather controls, X_{zt}, as in Equation 3 and add fixed effects for county by month to control for seasonality in mortality. Standard errors are two-way clustered at the county and state by year levels.

Table 5 reports the results of the mortality analysis. Across all ages (column 1), mortality in the month of exposure increases by 0.23 deaths per million individuals (panel A), with effects growing to 0.37 deaths per million within three months of exposure (panel B). Extending the mortality window to six months following exposure (panel C) yields a precisly measured mortality estimate of 1.5 deaths per million. Further extending the post-exposure window to a year produces a positive but insignicant estiamte of 0.92 (panel D). Taken together, these estimates indicate medium-run mortality effects of smoke that level off between 3 to 6 months following smoke exposure.

In columns 2 and 3 of Table 5 we report estimates of the mortality effect of smoke exposure sep-

arately by age group. We find mortality responses are concentrated among individuals aged 60 and older. Among this group, each day of smoke increases mortality by 1.8, 3.8, 9.3 and (imprecisely estimated) 4.0 deaths per million within 1, 3, 6, and 12 months of smoke exposure, respectively. The pattern suggests that the 6-month mortality estimates capture the extent of premature mortality from smoke, including potentially lagged effects. Any additional deaths at between 6 and 12 months are approximately equal to those deaths shifted from this period to the first 6 months following exposure.

To calculate the welfare cost of smoke mortality, we scale the age group-specific mortality effects by the average life expectancy among individuals in these groups and assume a $100,000 value for each year of life lost, following Deschênes and Greenstone (2011).[26] If individuals who die from smoke exposure are less healthy than average among their age group, this approach will generate an upper bound on welfare cost of smoke mortality. Because of the small and statistically insignificant effects among younger age groups, we assume a negligible mortality cost among all age groups except the oldest group.

Following this approach, we calculate the welfare cost of smoke mortality by multiplying the mortality effect of smoke among the population aged 60 and older (9.265 deaths per million per day of smoke), the average life expectancy among this population (16.1 years of life per death), the size of this population in millions (59.0, per 2012 U.S. Census), the average number of smoke days per year (17.7), and the value of a life-year ($100,000 per life-year lost). This generates an estimate of $15.6 billion in mortality costs due to wildfire smoke each year.

A key feature of the analysis is that we use the same measured variation in both the earnings and mortality analyses. The estimates from the labor market can then be directly compared with the mortality costs. We find that mortality costs ($15.6 billion) are approximately one-sixth of the lost labor market earnings ($93 billion). Our preferred estimate of $70 billion in welfare cost of these lost earnings implies that the labor market cost of air pollution due to wildfire smoke exposure is more than four times the mortality cost. Even taking our lower bound of $23 billion

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[26]We calculate average life expectancy within each age group from the 2014 period life table for the Social Security area population https://www.ssa.gov/oact/STATS/table4c6.html#ss (accessed on September, 2017).

in welfare cost due to lost earnings implies a labor market cost that is 1.5 times as large as the mortality cost. A smaller ratio would be estimated if we consider only earnings losses in the year of exposure; since most exposure occurs in the second half of the year, this more closely corresponds to the 6-month mortality window. Earnings losses in the same year represent between 0.6 and 1.7 times the costs to mortality. These welfare calculations demonstrate that lost labor market earnings represent a source of welfare losses that should be considered as large or larger than mortality costs, which are usually thought to comprise the majority of health costs. A full welfare accounting would consider elements such as medical costs, losses to firms, the deadweight loss of additional tax revenue required to make Social Security payments, as well as adaptive and defensive investments. However, the literature has traditionally focused on mortality as the primary driver of costs, and including these elements would not alter the primary conclusion, that labor market responses impose an important, or even primary, share of the welfare costs of wildfire smoke.

6   Discussion and Conclusion

Wildfires cause severe damage to the areas they burn, destroying homes and property and threatening human lives in their path. Wildfires also produce a harmful and prevalent source of air pollution, to which most of the U.S. population is exposed at some point each year. We analyze annual variation in wildfire smoke exposure across the United States and find that increases in smoke exposure cause significant decreases in earnings, which in turn are associated with decreased labor force participation and increases in Social Security benefits. These findings suggest that the impacts of reduced air quality on worker productivity do not just fall on firms, such as through higher sick leave expenses, but are at least partly passed on to workers in the form of lower earnings. In addition, we find that the welfare cost of these lost earnings is significantly larger than the cost of increased mortality due to the same wildfire smoke events.

The findings in this paper have broad implications for environmental policy and the grow-

ing body of literature on the labor market effects of air pollution. Many agencies that engage in environmental policy making, such as the WHO, OECD, World Bank, and EPA, have traditionally treated pollution damages arising from lost labor market hours and earnings as considerably smaller than the mortality cost of air pollution. Our results, which provide the first quasi-experimental evidence of the effect of air pollution events on labor markets at a national scale, indicate that environmental policies that ignore the labor market effects of air pollution ignore a significant cost, and may be designed inefficiently as a result. In addition, our results imply that the employment-reducing effects of environmental regulation are at least partially offset by earnings and employment gains to workers resulting from improved air quality. Although wildfire smoke has a different chemical composition from that of industrial pollution or vehicle exhaust, the large labor market costs of wildfire-emitted pollutants—which comprise a significant share of all U.S. particulate matter emissions—suggest that other EPA-monitored pollutants that negatively affect health may similarly have large labor market costs.

Our findings also have direct implications for wildfire policy and management. A primary implication of our results is that downwind labor market effects of wildfire smoke generation create large externalities in land use and fire management. These effects call for greater coordination of fire policy efforts, including a focus on preventing smoke-producing wildfires from starting and spreading in addition to the narrower goal of defending land and property exposed to fire damage. For example, fires generating large smoke plumes that may reach urban centers should be prioritized over fires that burn far from or downwind of population centers. Management of forest fires, which typically consume dense biomass and therefore generate large, thick smoke plumes, should be prioritized over fires that consume less biomass. The use of prescribed fires to remove fuel and limit the scope for larger future burns should likely expand, although such fires should be set only after taking into account wind patterns to avoid population exposure. Finally, estimates of the marginal cost of firefighting and prevention—which we note are sorely lacking in the literature—should consider both the cost of reducing acreage burned and the cost of reducing population smoke exposure. While wildfires and smoke cannot and should not be completely

eliminated, planning and optimal policy can mitigate damages from these events.

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Figure 1: County Annual Wildfire Smoke Exposure 2006–2015
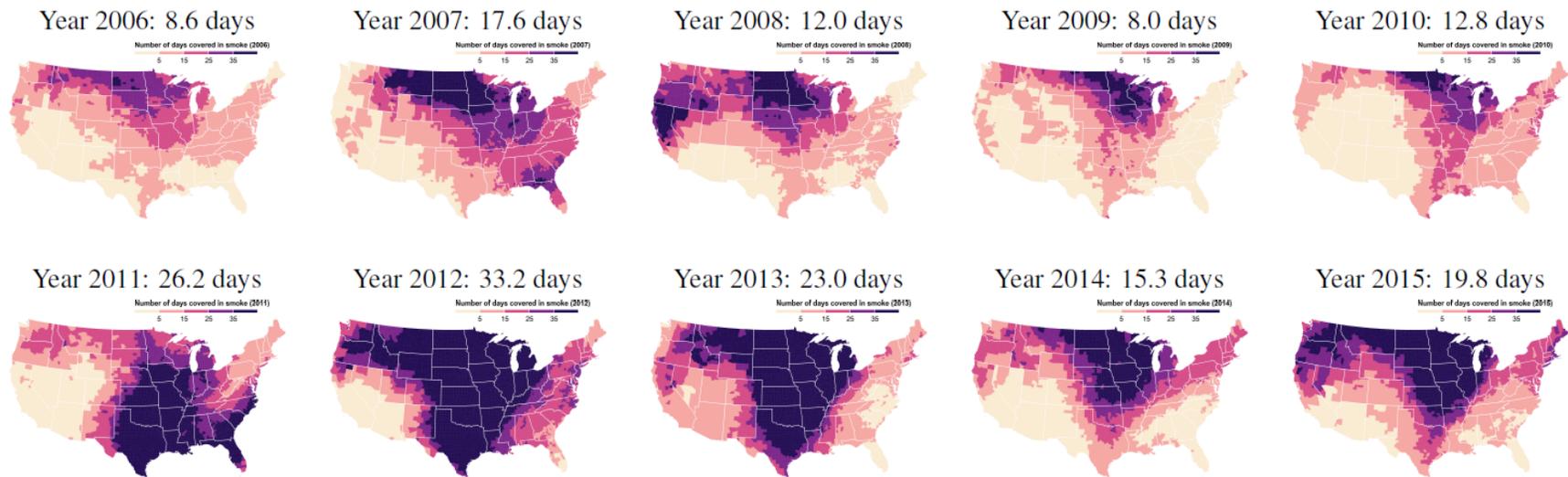
Notes: This figure plots county-level average annual days of smoke exposure for the lower 48 states for each year from 2006 to 2015. Average population-weighted exposure during this period was 17.7 days per year. Grayscale shading indicates quintiles of smoke exposure: 0–5 days (lightest shading), 6–15 days, 16–25 days, 26–35 days, or more than 35 days (darkest shading).

Figure 2: Daily Air Pollution Effects of Wildfire Smoke: Event Study
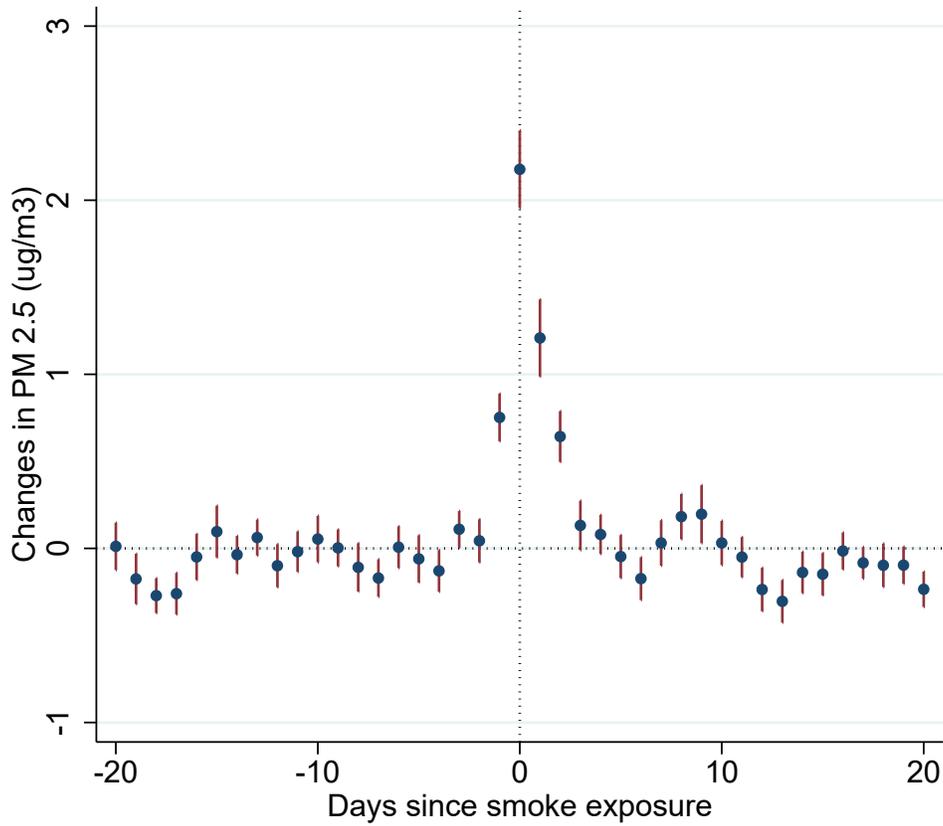
Notes: This figure shows coefficients from a regression of daily $PM_{2.5}$ on indicators of daily smoke exposure up to 20 days before and after the day of observation. In addition to the 41 smoke indicators, the regression controls for county-by-week-of-year fixed effects, state-by-year fixed effects, day-of-week fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic daily precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. Daily observations for years in which a county experienced a wildfire are excluded. Standard errors are clustered at both the county and the state-by-year levels.

Figure 3: Annual Wage Income Effect of Wildfire Smoke: Residualized Plot
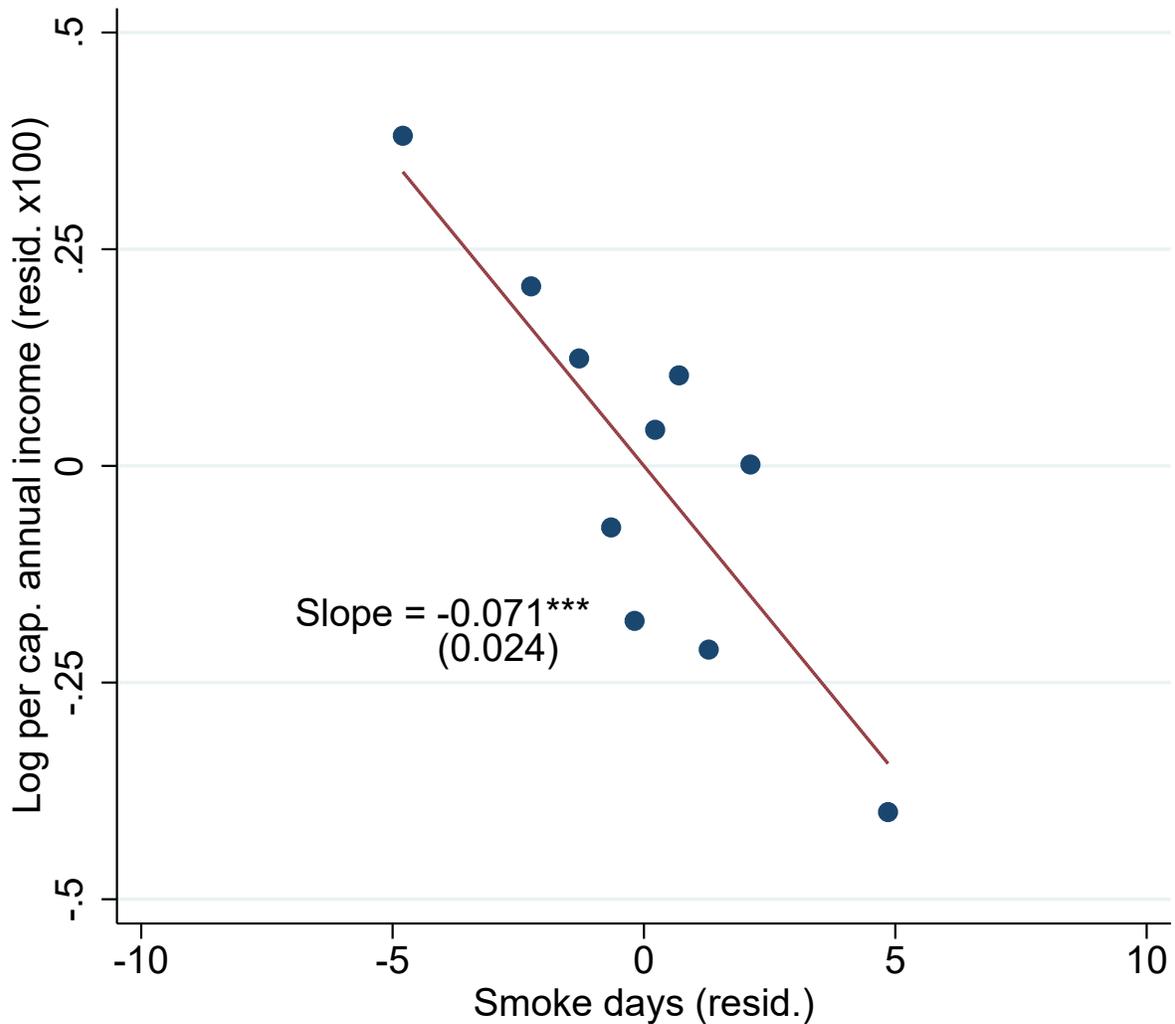
Notes: This graph shows a binscatter of residualized log per capita wage income by residualized annual smoke days. The dependent variable is the log of the average per capital annual income across IRS, CBP, REIS, and QWI data, scaled by 100. The focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. The slope coefficient in this graph reflects percentage changes in per capita income per day of smoke. All regressions include county fixed effects, state-by-year fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. All regressions exclude observations for years in which a county experienced a wildfire.

Figure 4: Annual Wage Income Effects of Wildfire Smoke: Industry Profile
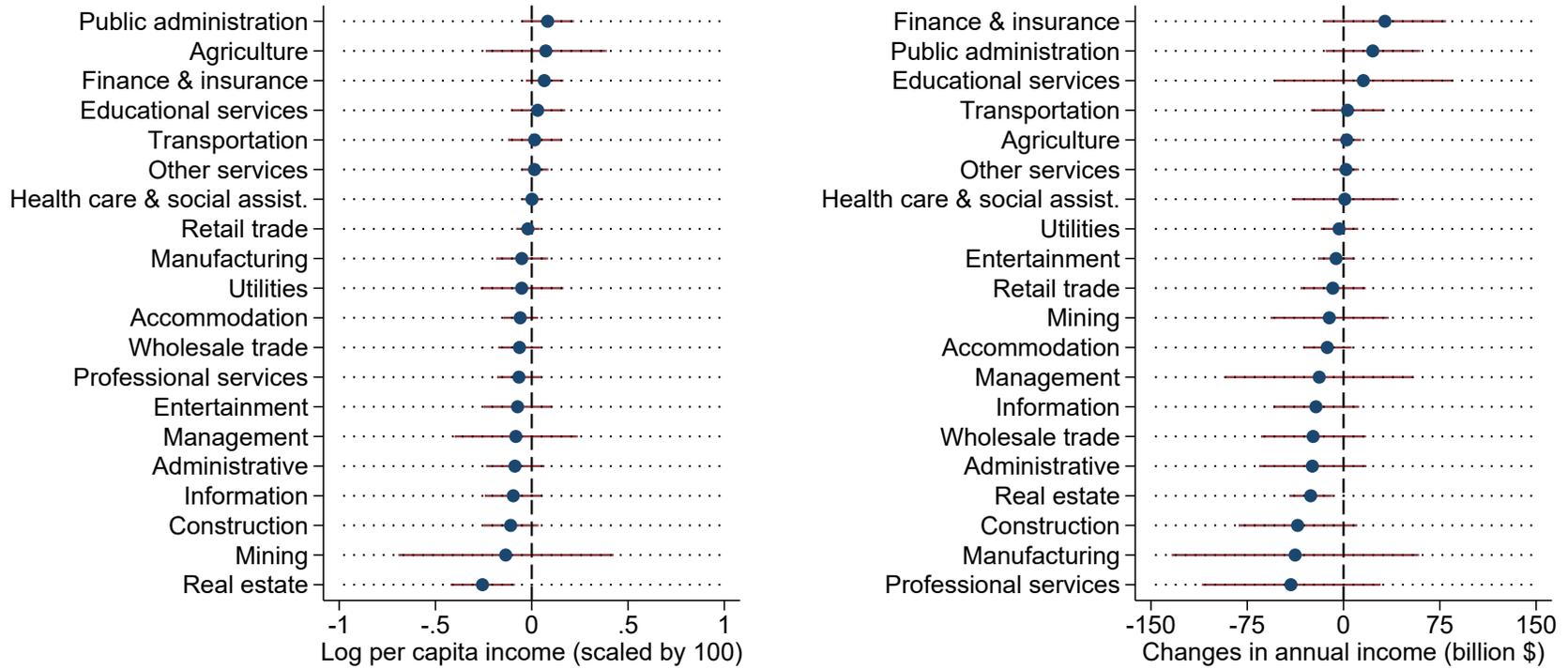
Notes: The figure reports estimated effects of an additional day of wildfire smoke exposure on log per capita (left) and economy-wide total (right) annual income separately for 2-digit NAICS industries. The focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. All regressions include county fixed effects, state-by-year fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. All regressions exclude observations for years in which a county experienced a wildfire. Standard errors are clustered at both the county and the state-by-year levels.

Table 1: Daily and Annual Air Pollution Effects of Wildfire Smoke

	(1)	(2)	(3)	(4)	(5)	(6)
Unit of measurement:	$PM_{2.5}$ ug/m3	PM_{10} ug/m3	O_3 ppb	CO ppb	NO_2 ppm	SO_2 ppm
Panel A. Daily effect						
1(Smoke)	2.173***	3.743***	3.162***	11.190***	0.530***	0.157***
	(0.118)	(0.179)	(0.147)	(1.063)	(0.068)	(0.022)
Mean dep. var.	10.38	21.11	27.39	360.17	11.89	1.94
SD dep. var.	6.02	13.26	10.59	172.16	7.57	2.53
Number of observations	2,338,609	1,347,701	3,640,761	1,594,882	1,714,565	2,566,112
Panel B. Annual effect						
Smoke days	0.019*	0.077**	0.032***	-0.413	-0.021*	0.007
	(0.010)	(0.037)	(0.010)	(0.636)	(0.012)	(0.006)
Mean dep. var.	10.26	20.68	27.83	358.64	11.73	1.93
SD dep. var.	2.12	6.26	3.77	109.60	4.99	1.52
Number of observations	11,040	7,428	12,766	4,516	4,937	7,249

Notes: The table reports estimated effects of a day of wildfire smoke on pollution that day (panel A) and an additional day of wildfire smoke exposure on annual pollution (panel B). Each panel-column corresponds to a separate regression using county-daily/annual observations and county population weights. Daily-level regressions include county-by-week-of-year fixed effects, state-by-year fixed effects, day-of-week fixed effects, 3 leads and 3 lags of smoke day indicators, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic daily precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. Annual-level regressions include county fixed effects, state-by-year fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. All regressions exclude observations for years in which a county experienced a wildfire. Standard errors are clustered at both the county and the state-by-year levels.

Table 2: Annual Wage Income Effect of Wildfire Smoke

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: log of per capita annual income (scaled by 100)							
Smoke days (year $t+1$)						-0.033	-0.026
						(0.021)	(0.018)
Smoke days (current year t)	-0.059**	-0.080***	-0.054**	-0.065***	-0.071***	-0.043**	-0.035*
	(0.026)	(0.029)	(0.027)	(0.025)	(0.024)	(0.018)	(0.018)
Smoke days (year $t-1$)						-0.069***	-0.038**
						(0.024)	(0.017)
Smoke days (year $t-2$)							-0.032*
							(0.018)
Wage data source	QWI	CBP	REIS	IRS	All	All	All
Mean per capita income	20,496	17,299	22,154	21,494	20,533	20,359	20,449
Number of observations	22,803	22,711	22,579	22,861	22,851	18,309	16,045

Notes: The table reports estimated effects of an additional day of wildfire smoke exposure on annual income. Each column corresponds to a separate regression using county-year observations and county population weights. In columns (1)–(4), the dependent variable is the log of per capita annual income as measured by the data source indicated in the bottom panel, scaled by 100. In columns (5)–(7), the dependent variable is the log of the average per capital annual income across all (four) data sources, scaled by 100. The means of per capita income are in 2010 dollars. The focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. Coefficients reflect percentage changes in per capita income per day of smoke. All regressions include county fixed effects, state-by-year fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. All regressions exclude observations for years in which a county experienced a wildfire. Standard errors are clustered at both the county and the state-by-year levels.

Table 3: Annual Employment and Retirement Effects of Wildfire Smoke

	(1)	(2)	(3)	(4)	(5)
	LFP (per million pop.16+)	Employment (per million pop.16+)	Employment (per million pop.55+)	Retire. & DI benefits (log per cap.$\times$100)	Retire. benefits (log per cap.$\times$100)
Smoke days (year $t+1$)	-17.0	-96.3	-96.0	0.009	0.009
	(137.8)	(119.7)	(75.1)	(0.019)	(0.022)
Smoke days (current year t)	-146.9*	-288.9***	-176.6***	0.026*	0.015
	(88.5)	(103.6)	(62.8)	(0.016)	(0.018)
Smoke days (year $t-1$)	-78.1	-153.6	-177.0**	0.037*	0.033
	(110.2)	(107.8)	(73.7)	(0.021)	(0.026)
Mean dep. var.	633,873	634,295	366,257	86.73	45.08
Data source:	BLS LAU	QWI	QWI(55+)	REIS	SSA
Number of observations	18,309	18,273	18,273	18,092	17,888

Notes: The table reports estimated effects of an additional day of wildfire smoke exposure on annual labor force participation, employment and retirement outcomes. Each column corresponds to a separate regression using county-year observations and relevant county population weights. The focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. In columns (1) (2) and (3), coefficients reflect changes in labor force participation and employment outcomes (counts per relevant population) per day of smoke. In columns (4) and (5), coefficients reflect percentage changes in per capita income receipt per day of smoke. All regressions include county fixed effects, state-by-year fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. All regressions exclude observations for years in which a county experienced a wildfire. Standard errors are clustered at both the county and the state-by-year levels.

Table 4: Heterogeneous Wage Income Effects of Wildfire Smoke

	(1)	(2)	(3)	(4)	(5)
Dependent variable: log of per capita annual income (scaled by 100)					
Characteristics k:	Frac. urban	Median home value	Frac. poverty	Frac. black	Avg. $PM_{2.5}$
Smoke days $\times$ $1(k <$median$)$	-0.015	-0.023	-0.035*	-0.034*	-0.038**
	(0.018)	(0.018)	(0.018)	(0.019)	(0.017)
Smoke days $\times$ $1(k \geq$median$)$	-0.049***	-0.049**	-0.050**	-0.052***	-0.040**
	(0.019)	(0.019)	(0.020)	(0.019)	(0.020)
p-value	0.000	0.006	0.061	0.061	0.748
Number of observations	18,309	18,309	18,309	18,309	10,139

Notes: The table reportes heterogeneous effects of an additional day of wildfire smoke exposure on annual wage income. Each column corresponds to a separate regression using county-year observations and relevant county population weights. The focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. Interaction terms are county-level above- and below-median indicators for fraction of urban population (column 1), median home value (column 2), fraction of population living under 100% of the Federal Poverty Line (column 3), fraction of population that is African American (column 4), average $PM_{2.5}$ during the study period (column 5). p-value corresponds to the null that there is no differential effect of smoke across above- and below-median groups. All regressions include county fixed effects, state-by-year fixed effects, one lead and one lag in smoke exposure, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. All regressions exclude observations for years in which a county experienced a wildfire. Standard errors are clustered at both the county and the state-by-year levels.

## Table 5: Monthly Mortality Effect of Wildfire Smoke

	(1)	(2)	(3)
	All-age	Ages below 60	Ages above 60
Panel A. 1-month mortality effect			
Smoke days	0.232**	0.091**	1.846***
	(0.110)	(0.042)	(0.573)
Mean dep. var.	703.2	173.7	2944.6
Panel B. 3-month mortality effect			
Smoke days	0.368	0.141	3.781***
	(0.262)	(0.087)	(1.241)
Mean dep. var.	2108.9	520.9	8846.3
Panel C. 6-month mortality effect			
Smoke days	1.499***	0.197	9.265***
	(0.536)	(0.143)	(2.453)
Mean dep. var.	4218.7	1041.7	17747.3
Panel D. 12-month mortality effect			
Smoke days	0.917	-0.118	4.043
	(0.642)	(0.227)	(2.958)
Mean dep. var.	8457.4	2082.6	35816.8
Avg. life years lost	44.5	50.4	16.1

Notes: The table reports estimated effects of an additional day of wildfire smoke exposure on monthly mortality rate. k-month mortality is the number of deaths in the next k months (including the current month) divided by relevant population. Each panel-column corresponds to a separate regression using county-monthly observations and relevant county population weights. The focal independent variables capture the number of days in a month on which a county was exposed to wildfire smoke. All regressions include county-by-month-of-year fixed effects, state-by-year fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic monthly precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. Regressions in panels B, C, and D control additionally for number of smoke days in the corresponding look-ahead windows. All regressions exclude observations for years in which a county experienced a wildfire. Standard errors are clustered at both the county and the state-by-year levels.

A   Online Appendix

## Online Appendix Figures and Tables

Figure A.1: Fire and Smoke on May 7, 2016
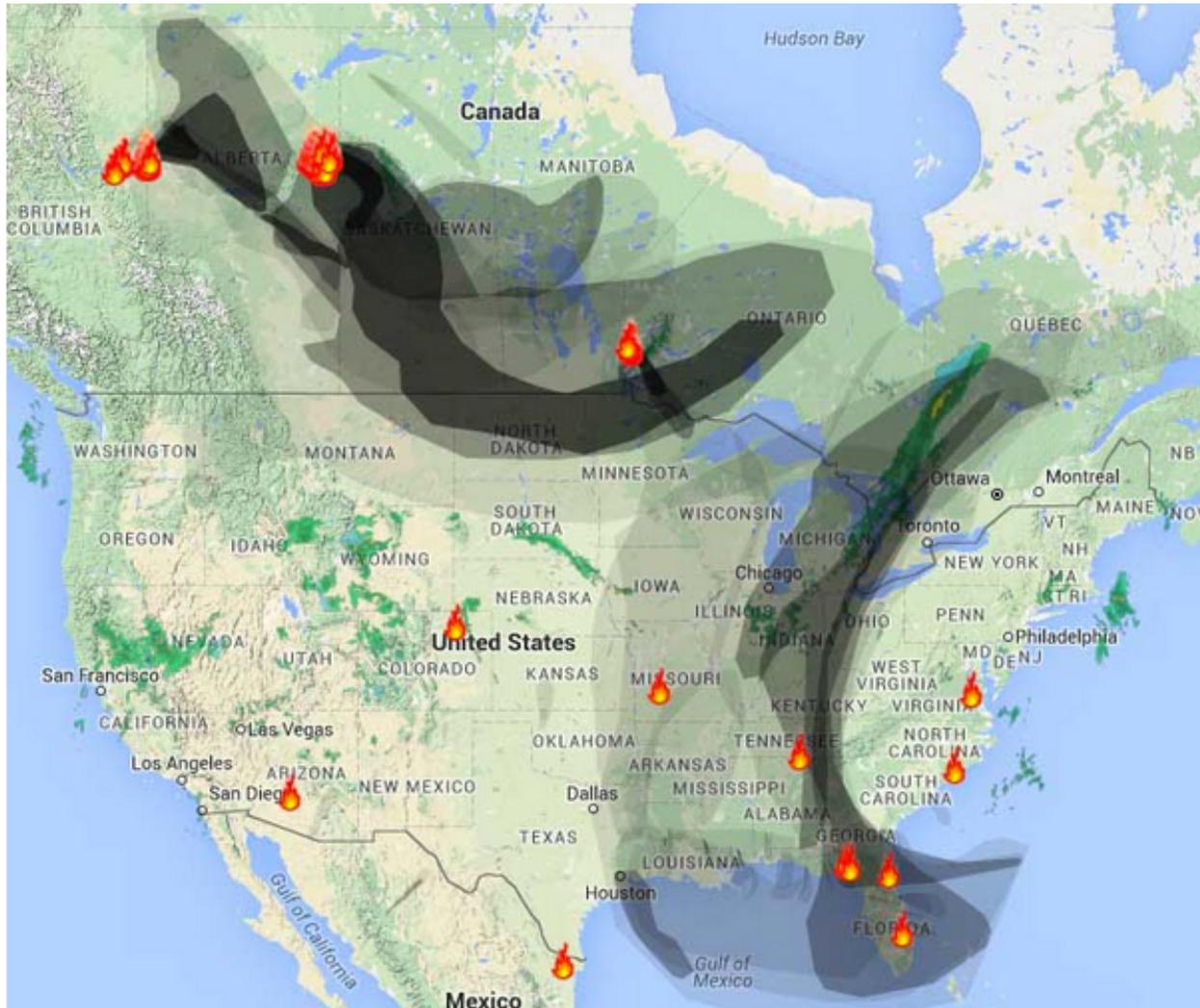
Notes: This map depicts smoke patterns on May 7, 2016 at 9:20 AM. The Fort McMurray fires in Northern Canada can be seen north of Alberta. This large wildfire produces a smoke plume that reaches the upper Midwest. Wildfires in the U.S. Southeast produce plumes reaching Canada. Source: WeatherUnderground.com via WildfireToday.com.

Figure A.2: County Annual Wildfire Exposure 2006 – 2015

Year 2006: 14.3 days Year 2007: 15.1 days Year 2008: 12.0 days Year 2009: 13.3 days Year 2010: 8.9 days

Year 2011: 12.0 days Year 2012: 12.9 days Year 2013: 16.9 days Year 2014: 9.7 days Year 2015: 9.4 days
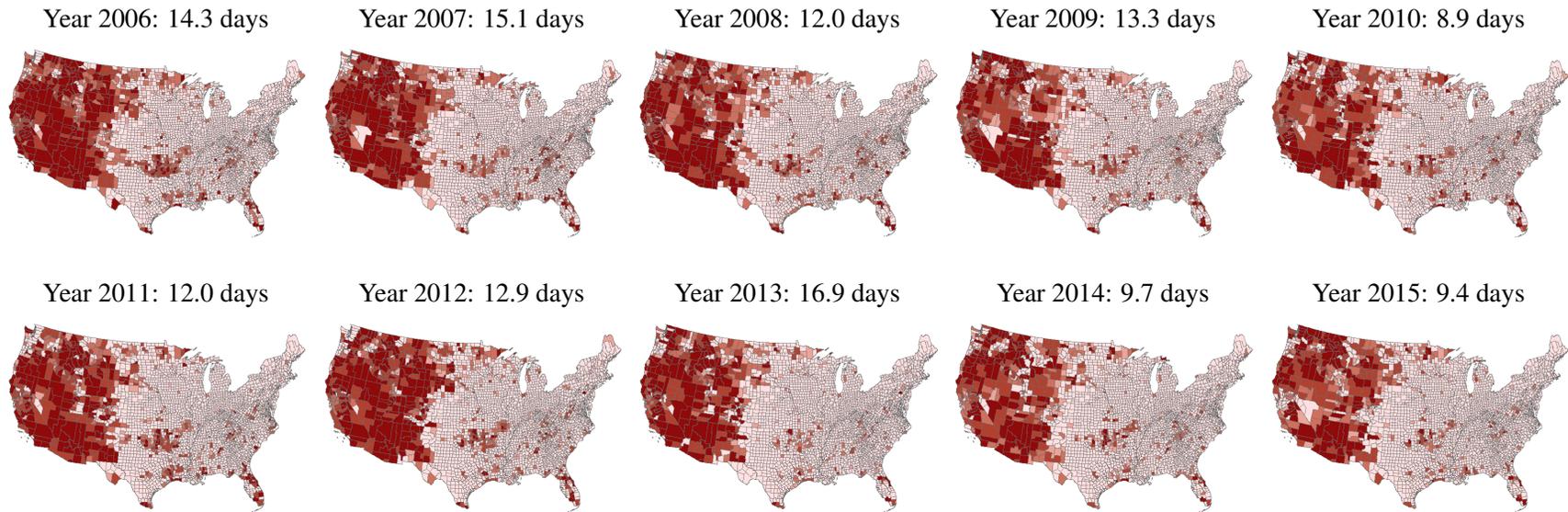
Notes: Notes: This figure plots county-level average annual days of wildfire exposure for the lower 48 states for each year from 2006 to 2015. Average exposure during this period was 20.1 days per year. Grayscale shading indicates of smoke exposure: 0 – 1 days (lightest shading), 1 – 3 days, 3 – 10 days, 10 – 33 days, or more than 33 days (darkest shading).

Figure A.3: Daily Air Pollution Effects of Wildfire Smoke: Robustness to Wind Controls
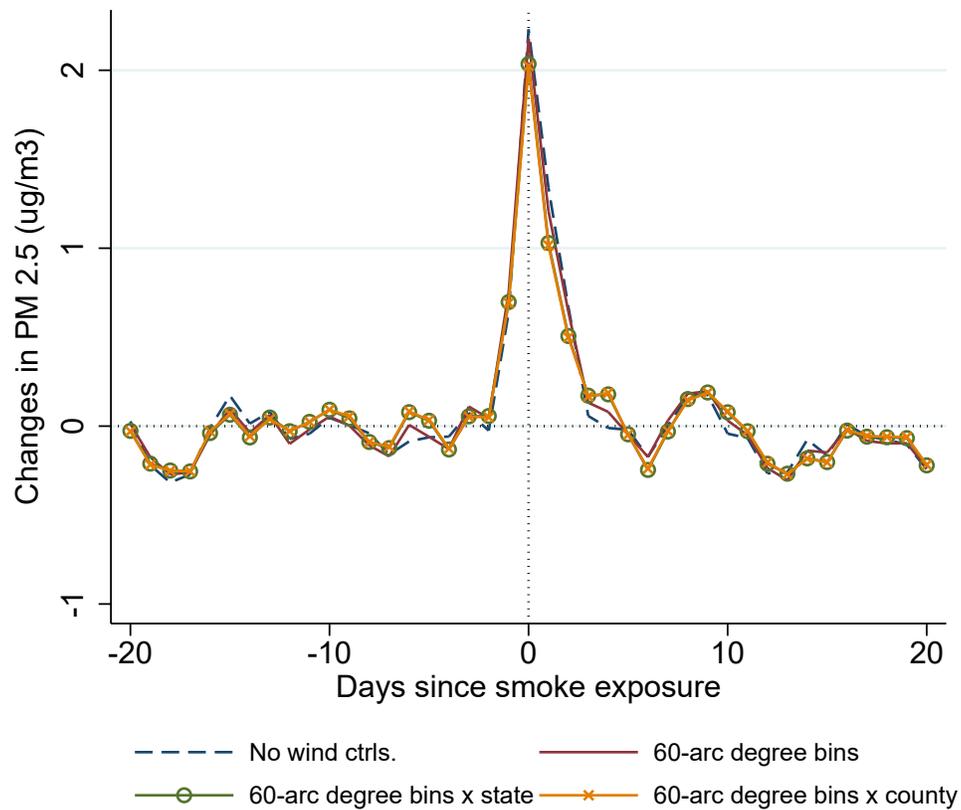
Notes: This figure shows coefficients from a regression of daily $PM_{2.5}$ on indicators of daily smoke exposure up to 20 days before and after the day of observation. Three specifications show varying degrees of controls of wind direction: no controls, 60-arc degree bins of daily wind direction, 60-arc degree bins of daily wind direction fully interacted with state dummies, and 60-arc degree bins of daily wind direction fully interacted with county dummies. In addition to the 41 smoke indicators, the regression controls for county-by-week-of-year fixed effects, state-by-year fixed effects, day-of-week fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic daily precipitation, and quintile bins of daily average wind speed. Daily observations for years in which a county experienced a wildfire are excluded. Standard errors are clustered at both the county and the state-by-year levels.

Figure A.4: Annual Employment Effects of Wildfire Smoke: Age Profile
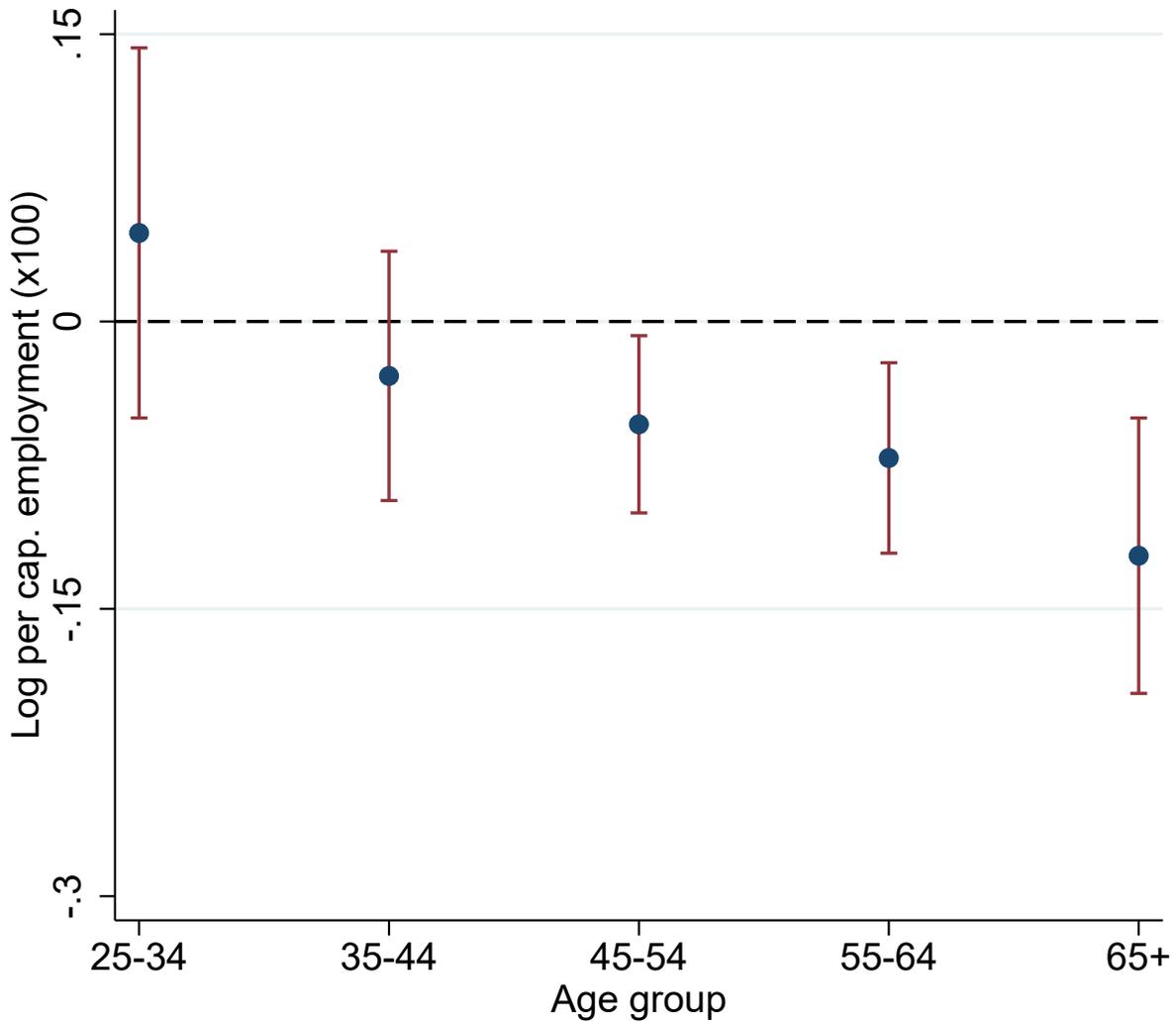
Notes: The figure reports estimated combined effects (current plus lagged effect) of an additional day of wildfire smoke exposure on annual employment per capita separately for different age groups. The dependent variable is the log of per capita employment as measured by QWI, scaled by 100. The focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. Coefficients reflect percentage changes in per capita employment per day of smoke in the relevant age group. All regressions include county fixed effects, state-by-year fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic daily precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. All regressions exclude observations for years in which a county experienced a wildfire. Standard errors are clustered at both the county and the state-by-year levels.

Table A.1: Annual Migration Effect of Wildfire Smoke

	(1)	(2)	(3)
	Log per capita in-migrants (scaled by 100)	Log per capita out-migrants (scaled by 100)	Log number of tax exemptions (scaled by 100)
Smoke days	0.005	0.003	0.038
	(0.018)	(0.016)	(0.025)
Number of observations	22,829	22,831	22,851

Notes: The table reports estimated effects of an additional day of wildfire smoke exposure on annual migration. Each column corresponds to a separate regression using county-year observations and relevant county population weights. The focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. All regressions include county fixed effects, state-by-year fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. All regressions exclude observations for years in which a county experienced a wildfire. Standard errors are clustered at both the county and the state-by-year levels.

Table A.2: Annual Income Effect of Wildfire Smoke: Alternative Smoke Definitions

	(1)	(2)	(3)
Smoke definition:	Sum of daily coverage	Days with coverage $\geq$ 75%	Days with entire coverage
Smoke days	-0.053**	-0.060***	-0.071***
	(0.022)	(0.023)	(0.024)
Mean annual smoke days	23.8	22.2	20.4
Number of observations	22,851	22,851	22,851

Notes: The table reports estimated effects of an additional day of wildfire smoke exposure on earning. Each column corresponds to a separate regression using a different smoke measure. For example, in column 2, we count days when a county is at least 75% covered in smoke, where 75% is the average coverage rate conditional on any smoke coverage. The focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. All regressions include county fixed effects, state-by-year fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. All regressions exclude observations for years in which a county experienced a wildfire. Standard errors are clustered at both the county and the state-by-year levels.

Table A.3: Annual Wage Income Effect of Wildfire Smoke (including county-years with wildfires)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: log of per capita annual income (scaled by 100)							
Smoke days (year $t+1$)						-0.014	0.001
						(0.015)	(0.015)
Smoke days (current year t)	-0.035	-0.031*	-0.021	-0.040**	-0.036**	-0.036**	-0.033*
	(0.021)	(0.019)	(0.021)	(0.017)	(0.017)	(0.016)	(0.019)
Smoke days (year $t-1$)						-0.038**	-0.031*
						(0.015)	(0.016)
Smoke days (year $t-2$)							-0.015
							(0.012)
Wage data source	QWI	CBP	REIS	IRS	All	All	All
Mean per capita income	19,758	16,525	21,405	21,010	19,829	19,653	19,728
Number of observations	30,615	30,469	30,329	30,691	30,675	24,544	21,472

Notes: The table reports estimated effects of an additional day of wildfire smoke exposure on annual income. Each column corresponds to a separate regression using county-year observations and county population weights. In columns (1)–(4), the dependent variable is the log of per capita annual income as measured by the data source indicated in the bottom panel, scaled by 100. In columns (5)–(7), the dependent variable is the log of the average per capital annual income across all (four) data sources, scaled by 100. The means of per capita income are in 2010 dollars. The focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. Coefficients reflect percentage changes in per capita income per day of smoke. All regressions include county fixed effects, state-by-year fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. Standard errors are clustered at both the county and the state-by-year levels.

Table A.4: Annual Wage Income Effect of Wildfire Smoke: Robustness

	(1)	(2)	(3)	(4)	(5)
Wage data source	QWI	CBP	REIS	IRS	All
Alternative SE clustering	-0.059	-0.080	-0.054	-0.065	-0.071
... county & state×year levels	(0.026)**	(0.029)***	(0.027)***	(0.025)***	(0.024)***
... county & census division×year levels	(0.026)**	(0.031)**	(0.028)*	(0.025)**	(0.025)***
... county level	(0.025)**	(0.026)***	(0.021)**	(0.015)***	(0.017)***
... state level	(0.024)**	(0.038)**	(0.035)	(0.035)*	(0.034)**

Notes: The table reports estimated effects of an additional day of wildfire smoke exposure on annual income. Each column corresponds to a separate regression using county-year observations and county population weights. In columns (1)–(4), the dependent variable is the log of per capita annual income as measured by the data source indicated in the bottom panel, scaled by 100. In column (5), the dependent variable is the log of the average per capital annual income across all (four) data sources, scaled by 100. The focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. Coefficients reflect percentage changes in per capita income per day of smoke. All regressions include county fixed effects, state-by-year fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. Unless noted otherwise, all regressions exclude observations for years in which a county experienced a wildfire, with standard errors clustered at both the county and the state-by-year levels.

Table A.5: Robustness to Wind Direction Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	Daily PM$_{2.5}$			Annual PM$_{2.5}$			Annual income		
1(Smoke)	2.234***	2.173***	2.079***						
	(0.138)	(0.118)	(0.114)						
Smoke days				0.019*	0.019*	0.021***	-0.071***	-0.071***	-0.065***
				(0.010)	(0.010)	(0.007)	(0.024)	(0.024)	(0.023)
Wind controls									
None	✓			✓			✓		
60-arc degree bins		✓			✓			✓	
60-arc degree bins×state			✓			✓			✓

Notes: The table reports estimated effects of a day of wildfire smoke on pollution that day (columns 1–3) and an additional day of wildfire smoke exposure on annual pollution and income (columns 4-9). In columns (7)–(9), the dependent variable is the log of per capital annual income, scaled by 100. Each column corresponds to a separate regression using county-daily/annual observations and county population weights. Daily-level regressions include county-by-week-of-year fixed effects, state-by-year fixed effects, day-of-week fixed effects, 3 leads and 3 lags of smoke day indicators, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic daily precipitation, and quintile bins of daily average wind speed. Annual-level regressions include county fixed effects, state-by-year fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, and quintile bins of daily average wind speed. All regressions exclude observations for years in which a county experienced a wildfire. Standard errors are clustered at both the county and the state-by-year levels.